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FLOW STRESS PREDICTION OF HOT COMPRESSED TOOL STEEL BY CAE NN AND HYPERBOLIC-SINE EQUATION

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Hot compression experiments are carried out on steel workpieces by means of Gleeble 1500 thermo mechanical simulator in wide range of temperatures 800 °C - 1200 °C with strain rates 0,1 s^{-1}, 1,0 s^{-1} and 8,0 s^{-1} and true strains of 0,0 to 0,5. Hot flow curves were estimated by means of the CAE neural networks. The methods of constant smoothness parameter and non-constant (ellipsoidal) smoothness parameter were applied. The use of the latter proved more exact (up to 3,4 %) and simpler if we compare it with the existing data for the flow curve prediction of tool steel by BP NN (up to 7 %), as the proposed method yields better results. The activation energy and other parameters in hyperbolic-sine equation were calculated according to the method proposed by McQueen et al. and according to the method recently proposed by Kugler et al. The latter yields better results at predicting the maximum values of hot flow curves.

Key words: *tool steel, hot compression, flow stress, artificial neural network, activation energy*

Predmnijevanje napona naprezanja kod vrućeg sabijanja čelika s CAE NN i hiperboličnom - sinusoidnom jednadžbom. Pomoću termomehaničkog simulatora Gleeble 1500 izvedeni su vrući pokusi sabijanja čeličnih proba u temperaturnom rasponu 800 °C - 1200 °C, brzinom deformacije 0,1 s^{-1}, 1,0 s^{-1} i 8,0 s^{-1} i stupnja deformacije od 0,0 do 0,5. Naprezanja materijala određena su pomoću CAE neuralnih mreža. Rabljene su metode stalnog i nestalnog (elipsoidnog) parametra glatkoće. Upotreba zadnjih pokazala se za točniju (do 3,4 %) i jednostavniju ako ih se usporedi s znanima podacima krivulje naprezanja alatnog čelika metodom BP NN (do 7 %). Aktivacijska metoda i ostali parametri u hiperbolično - sinusoidnoj jednadžbi izračunani su metodom koju predlaže McQueen i ostali te novijom metodom predloženoj od Kuglera i ostalih. Ta zadnja ima bolje rezultate za predmnijevanje maksimalnih vrijednosti krivulja tečenja u vrućem.

Ključne riječi: *alatni čelik, vruće sabijanje, krivulja tečenja, umjetne neuralne mreže, aktivacijska energija*

INTRODUCTION

By the technology of hot forming - due to demands for maintaining the competitive position - there are constant demands for reduction of the prime costs, for improvement of products quality and for increasing of productivity. In order to make it possible for the technologists to achieve that in practice, the researchers must improve the models for prediction of material behaviour during the hot forming and make the simple for application. The flow curves of the formed material are here as important as hot plasticity [1 - 5]. To achieve the best possible description of flow curves during the hot forming of metals many models have been proposed so far. At classical functional records we calculate the model constants from the given database. It is known that the influences of most factors on flow curves are not linear; therefore the predicted capability of the models is limited and ranges from 2 to 60 %. In case of additional experimental data on flow curves or in case of needed additional parameters we must furthermore calculate the model constants anew [5 - 11]. In spite of great progress physical models are still rather limited to the relatively pure metals and as such have not yet been sufficiently accepted into practice [12]. Due to the known fact that the path leading form empirical to physical models will take a longer time, some researchers, whose aim is to achieve better prediction of hot flow curves, started using alternative paths, e.g. Back Propagation Neural Networks (BP NN). Due to relatively big difficulties in determining the optimal architecture of layers when applying the BP NN, limited number of input parameters, etc., there have been successful cases of using the CAE neural networks [5]. In comparison to regression

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models, the application of neural networks does not limit us neither with beforehand obligatory law of the mathematical model nor with non-linear character of some factors. In case of enlargement of database, the ANN can adjust the state of the old network to fit the new experimental data, instead of abounding or re-doing the old data or network [13 - 18]. The present demand regarding the flow curves, e.g. in the process of hot rolling, lies within the rate of 5 %. Striving for higher productivity and lower costs of a successful production makes it reasonable to go on with the experimental determination (verification) of flow curves. Experiences have shown that data of older type are not reliable because they do not contain exact data on stability of thermo mechanical testing, and furthermore the exact initial microstructure of applied work piece is very seldom given. Efficiency in numerical simulations of forming processes depends also on exactitude of constitutive equations for modelling of hot flow curves [17 - 21].

In our paper we compare the experimentally obtained flow curves for tool steel with the curves predicted by means of the CAE NN method. We used the methods of constant and non-constant smoothness parameter. Activation energy and other parameters in hyperbolic-sine equation were calculated according to the McQueen et al. method [22 - 24] as well as to the Kugler et al. method [25].

DESCRIPTION OF APPLIED MATERIAL AND EXPERIMENTAL PROCEDURE

The experimental flow curves were obtained by means of hot compression tests (Figure 1.), which were performed by the Gleeble 1500 thermo mechanical simulator. Chemical composition of applied tool steel is represented in Table 1. The samples with dimension of ∅ 8 mm × 12 mm were cut out of a rolled piece with ∅ 20 mm. The initial microstructure of applied samples is given in Figure 2. The following parameters regarding time were measured: compression force, temperature of cylindrical sample, shift of active jaws (sample height), diameter of cylindrical sample during compression. The strain rate was programmed as a constant value. These data were the basis for calculating of the tension and strain. The testing conditions of hot compression of cylindrical samples are given in Table 2. Testing was performed within the temperature range 800 - 1200 °C and strain rate range 0,1 – 1,0 – 8,0 s^{-1}, samples were programme-heated (Figure 3.). The velocity of heating amounted to °3 °C/s and was followed by 3 minutes of holding, i.e. annealing at 1200 °C, followed by cooling at speed of 2 °C/s to the deformation temperature and again by 30 s of holding, i.e. annealing at chosen deformation temperature. After the deformation the samples were quenched with water.

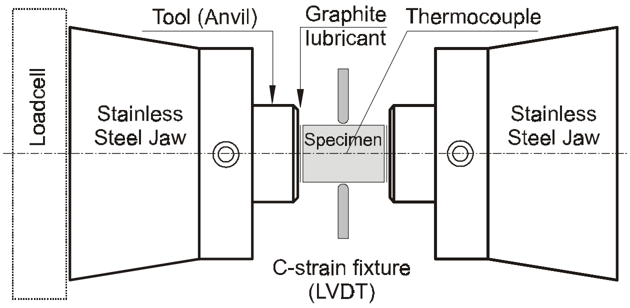

Figure 1. **Outline of hot compression test and measured parameters**
Slika 1. **Nacrt vrućeg pokusa sabijanjem s mjernim parametrima**

Table 1. **Chemical composition of applied steel (wt. %)**
Tablica 1. **Kemijski sastav upotrebljenog čelika (mas. %)**

C	S	Si	Cr	Ni	V
0,36	0,021	0,24	0,81	0,17	0,15
Al	Cu	Mn	Mo	P	Sn
0,040	0,24	0,68	0,05	0,011	0,017

Table 2. **Values of main testing parameters**
Tablica 2. **Vrijednosti glavnih parametara ispitivanja**

Tool steel	Ta	Temp. range	Strain rate s^{-1}
	1200 °C	800 - 1200 °C	0,1, 1,0, 8,0

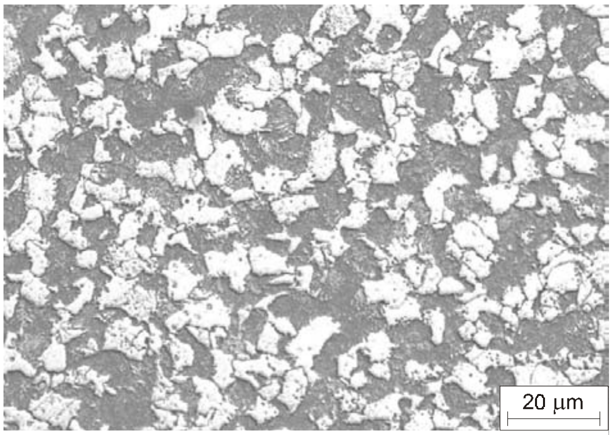

Figure 2. **Initial microstructures of applied tool steel (ferrite grains and laminar perlite grains)**
Slika 2. **Početna mikrostruktura upotrebljenog alatnog čelika (feritna zrna i zrna laminarnog perlita)**

PREDICTION OF THE FLOW STRESSES

CAE Neural Network

The problem addressed in this paper is how to estimate the flow stress curves (σ) as a function of known parameters, i.e. strain (ε), strain rate ($\dot{\varepsilon}$) and temperature (T). The first and second set of variables will be called the output and input variables, respectively.

In order to determine unknown output variables from known input variables, a data base containing sufficient well-distributed and reliable empirical data is needed. The data base should include both measured values of output variables and the corresponding input variables. One particular observation which is included in the data base can be described by a model vector. The input and output variables correspond to the components of this vector. For example, if at the strain 0,28, at the strain rate 3,5 s^{-1} and at the temperature 943 °C corresponding measured stress is 339 MPa, then the corresponding model vector is defined as {0,28, 3,5, 943; 339}.

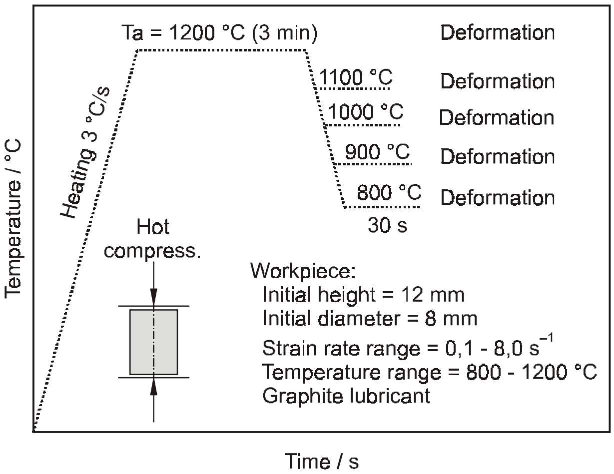

Figure 3. **Outline of temperature course in the tested cylindrical samples**
Slika 3. **Shema toka temperature za ispitivani cilindrični uzorak**

The real data base consists of a finite set of model vectors. According to the CAE method, each of the output variables corresponding to the model vector under consideration (i.e. a vector with known input variables and output variables to be predicted) can be estimated by the formulae [26]:

$$\hat{r}_k = \sum_{n=1}^{N} A_n \cdot r_{nk} \tag{1}$$

where

$$A_n = \frac{a_n}{\sum_{j=1}^{N} a_j} \tag{2}$$

and

$$a_n = \exp\left[\frac{-\sum_{i=1}^{L}\left(p_i - p_{ni}\right)^2}{2w^2}\right] \tag{3a}$$

Here $\hat{r}_k$ is the estimated (predicted) k-th output variable (e.g. *stress*, denoted as σ), r_{nk} is the same output variable corresponding to the n-th vector in the data base, N is the number of vectors in the data base, p_{ni} is the i-th input variable of the n-th vector in the data base (e.g. *temperature, strain, strain rate*), p_i is the i-th input variable corresponding to the vector under consideration, and L is the number of input variables.

In case of predicting flow stress curves, equation (3a) can be explicitly written as

$$a_n = \exp\left[-\frac{\left(\varepsilon_i - \varepsilon_{ni}\right)^2 + \left(\dot{\varepsilon}_i - \dot{\varepsilon}_{ni}\right)^2 + \left(T_i - T_{ni}\right)^2}{2w^2}\right] \tag{3b}$$

where ε denotes strain, $\dot{\varepsilon}$ strain rate and T temperature. Equation (1) suggests that the estimate of an output variable is computed as a combination of all output variables in the data base. Their weights depend on the similarity between the input variables p_i of the vector under consideration, and the corresponding input variables p_{ni} pertinent to the sample vectors stored in the data base. A_n is a measure of similarity.

Consequently, the unknown output variable is determined in such a way that the computed vector composed of given and estimated data is most consistent with the sample vectors in the data base.

The parameter w is the width of Gaussian function and is called the smoothness parameter. It determines how fast the influence of data in the sample space decreases with increasing distance from the point whose co-ordinates are determined by the components (input variables) of the vector under consideration. The larger the value of w is, the more slowly this influence decreases. Large w values exhibit an averaging effect. In principle, a proper value of w should correspond to a typical distance between data points. In this case the CAE method yields a smooth interpolation of functional relation between the input and output variables.

In some applications, as will be shown later, a non-constant value of w yields more reasonable results than a constant value. When using non-constant w values, equation (1) can still be used, but proper, locally estimated values of w_i should be taken into account. The formula for a_n (see Equation 3a) can be rewritten as

$$a_n = \exp\left[-\sum_{i=1}^{L}\frac{\left(p_i - p_{ni}\right)^2}{2w_i^2}\right] \tag{4a}$$

where different values of w_i correspond to different input variables. Equation (3b) can be rewritten accordingly as

$$a_n = \exp\left[-\frac{(\varepsilon_i - \varepsilon_{ni})^2}{2w_\varepsilon^2} - \frac{(\dot{\varepsilon}_i - \dot{\varepsilon}_{ni})^2}{2w_{\dot{\varepsilon}}^2} - \frac{(T_i - T_{ni})^2}{2w_T^2}\right] \quad (4b)$$

It should be noted that equations (1 - 3) were mathematically derived [26 - 28], based on the assumption of a constant uncertainty of the input data. The extension of the applicability of these equations to non-constant *w* values (4) is, however, based on physical considerations. Whereas a constant *w* corresponds to a sphere in an L-dimensional space (*L* is the number of input variables), corresponds a non-constant *w* value to a multi-axial ellipsoid in the same space [29, 30].

The choice of an appropriate value of *w* depends, as well as on the distribution of data, on the latter's accuracy and on the sensitivity of the output variables to changes in the input variables. Some engineering judgment, based on knowledge of the investigated phenomenon, and a trial and error procedure, are needed to determine appropriate value(s) for *w*.

The latest research has shown that the accuracy of the prediction can be related to the data distribution. A new measure, so called *local density of data distribution*, was proposed as a measure of quality of the prediction. It was introduced in order to detect the possible inaccurate predictions due to the improper data distribution and extrapolation outside the data range, and can be described by

$$\hat{\Theta}_k = \sum_{j=1}^{N} a_j \quad (5a)$$

Note that expression Σa_j from (5a) gives the number of model vectors in the vicinity of the unknown output variable $\hat{\delta}$. This is exact number of model vectors in limit case ($w \to 0$), while for larger *w* values the expression gives averaged number of model vectors. For comparison with the statistical density distribution, the measure can be normalized with its maximum value over the sample space (In this case the information of absolute distances over the sample space is lost):

$$\hat{\rho}_k = \frac{\sum_{j=1}^{N} a_j}{\max\left[\sum_{j=1}^{N} a_j\right]_k} \quad (5b)$$

Original proposal of the procedure [26], which in its extended form is called CAE and is presented here, consists of two parts. First part corresponds to the so-called self-organisation of the neurons. In cases of using relative small databases, this part is not needed. The second part represents the mathematical description of different phenomena, using optimal estimator, as described above. From this point of view the training (i.e. learning) represents simple presentation of the data to the CAE neural network. In addition, compared to the classical back-propagation neural networks (BP NN), testing the model is much simpler. Instead of using approximately 70 % of the data for training and the rest 30 % of the data for testing, different approach was used. Predicted parameter, i.e. stress of the *stress-temperature-strain-strain rate* curve was predicted for each point. In this process the model vector under consideration was temporarily removed from the database. By several trials optimal values of smoothness parameter were obtained. Recently, tests on very different phenomenon [30] than that presented here, show that such estimation of the efficiency of the proposed models in general gives more conservative estimates than classical approach.

For quality estimation of the efficiency of the CAE method by the prediction of flow curves we used the equation that calculates the root mean sum of the squared deviations (RMSSD) for each deformation condition:

$$RMSSD = \sqrt{\frac{\sum_{i=1}^{N} (\hat{\sigma}_k - \sigma_k)}{N}} \quad (6)$$

The prediction is considered good if the RMSSD value is within 5 % of the mean flow stress for that experimental condition [11]. The mean flow stress σ_{mfs} is calculated as

$$\sigma_{mfs} = \frac{1}{\varepsilon} \int \sigma \, d\varepsilon \quad (7)$$

APPLICATION FOR STEEL

Prediction of flow stress curves by CAE NN approach

The true flow stress curves of tool steel at different temperatures and different strain rates are presented in Figure 4. The flow stresses increase quickly with increase of strain until they reach a fixed value. During hot deformation is presented the process of dynamic recrystallization (DRX) [18, 19] that is clearly seen at higher temperature and lower strain rates.

The relations between the input and output variables are relatively simple and therefore a constant smoothing parameter can be used expression (3). However, its value must not be too small, since the generalization of the results may be lost. Results for material show relatively good agreement between the experimental and predicted results.

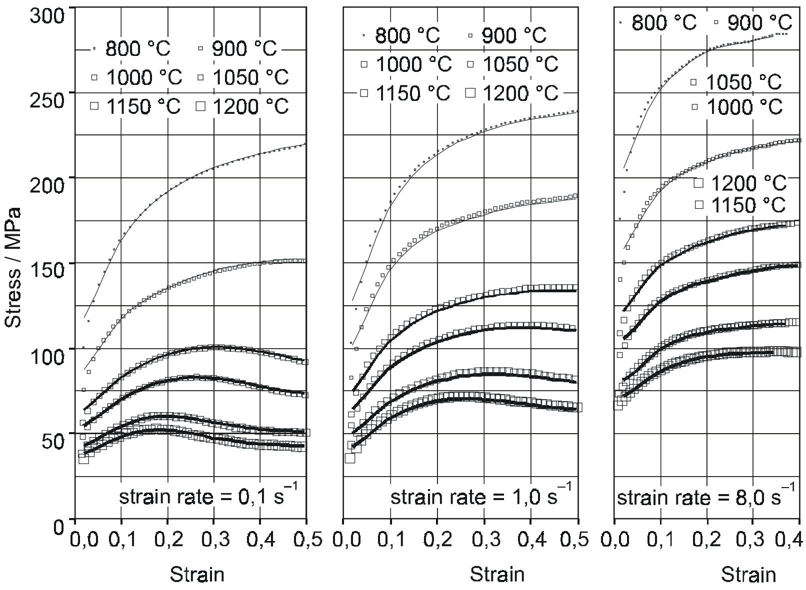

Figure 4. **Hot flow curves for tool steel - experimental and predicted results, using a constant smoothing parameter (w = 0,035)**

Slika 4. **Krivulje zatezanja u vrućem za alatni čelik - eksperimentalni i predmnijevani rezultati upotrebom stalnog parametra glatkoće (w = 0,035)**

Figure 4. shows the stress-strain relations for different temperatures between 900 °C and 1200 °C for three different strain rates at 0,1 s^{-1}, 1,0 s^{-1} and 8,0 s^{-1}, respectively. Due to the large distances in the direction of strain rate, some minor differences appear, most noticeable in case of strain rate of 1,0 s^{-1}. In addition, minor differences appear in case of small strains. The results can be improved by using smaller value of smoothness parameter, but in this case the ability of generalization of results is lost. This then results as the poor overall behaviour of the proposed model, especially interpolation in strain rate direction which produce non-smooth solution. The accuracy attained with the training data ranges from 0,9 % to 2,1 %, with an average error of 1,5 %. The accuracy of prediction on the testing data ranges from 1,2 % to 3,0 %, with an average error of 2,3 %. The errors arising are on average within the required accuracy limit.

Figure 5. clearly shows improvement in the strain range, especially in the range from 0,02 to 0,1 and at strain rate of 1,0 s^{-1}. The results suggest that modelling the flow stress curves may be improved by using a non-constant smoothing parameter (4). The accuracy achieved with the training data ranges from 0,1 % to 0,3 %, with an average error of around 0,2 %. The accuracy of prediction on the testing data ranges from 0,2 % to 3,4 %, with an average error of 1,0 %. The errors arising are well within the required accuracy limit [14], and are smaller than that obtained by classical BP neural networks [3, 4]. However, in order to get smoother solution (additional criterion), the value of smoothing parameter must be increased in some cases (Figure 6.).

The ability of CAE NN to interpolate is demonstrated by predicting flow stress at temperatures and strain spread over the entire domain in which the model is trained. Figure 6. shows a 3-D figure of flow stresses as a function of temperature and strain at different strain rates. Note, however, that the solution for w_T = 0,035 was a little bit unsmooth, and therefore larger value of w_T was applied. In the temperature range between 1000 °C and 1200 °C an explicit increase of flow stress values at 0,1 s^{-1} strain rate is evident; at 1 s^{-1} there is a transition to a less explicit increase in flow stress, and at the strain rate of 8,0 s^{-1} the increase in flow stress versus temperature becomes almost linear.

It should be noted some faults in the flow stress curve for a strain rate 8,0 s^{-1} at higher strains where experimental results were not available. These errors are due to extrapolation outside the range of the available data and can be clearly recognized by the calculation of data density distribution, using equation (5b). When $\hat{\rho}_k$ falls close to zero

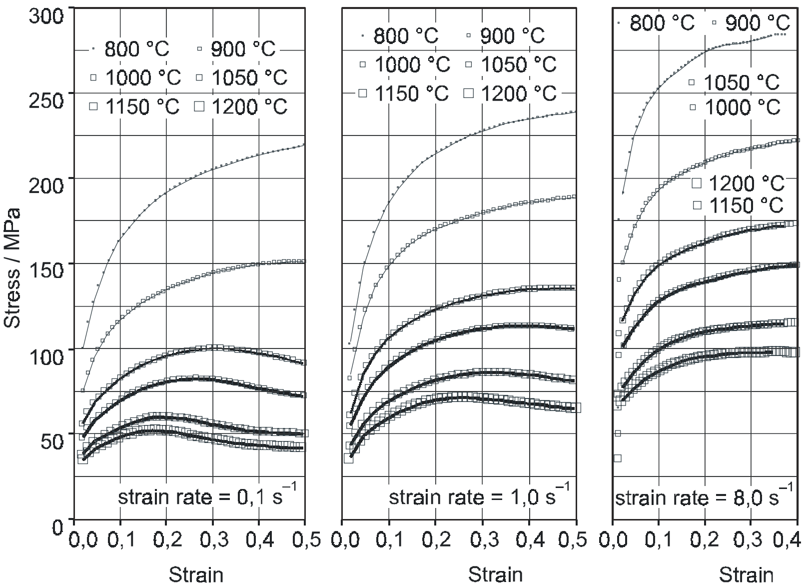

Figure 5. **Hot flow curves for tool steel - experimental and predicted results, using a non-constant smoothing parameter ($w_{\varepsilon(\varepsilon=0,01)}$ = 0,005; $w_{\varepsilon(\varepsilon=0,52)}$ = 0,015; $w_{\varepsilon'}$ = 0,005; w_T = 0,035)**

Slika 5. **Krivulje zatezanja u vrućem za alatni čelik - eksperimentalni i predmnijevani rezultati upotrebom nestalnog parametra glatkoće ($w_{\varepsilon(\varepsilon=0,01)}$ = 0,005; $w_{\varepsilon(\varepsilon=0,52)}$ = 0,015; $w_{\varepsilon'}$ = 0,005; w_T = 0,035)**

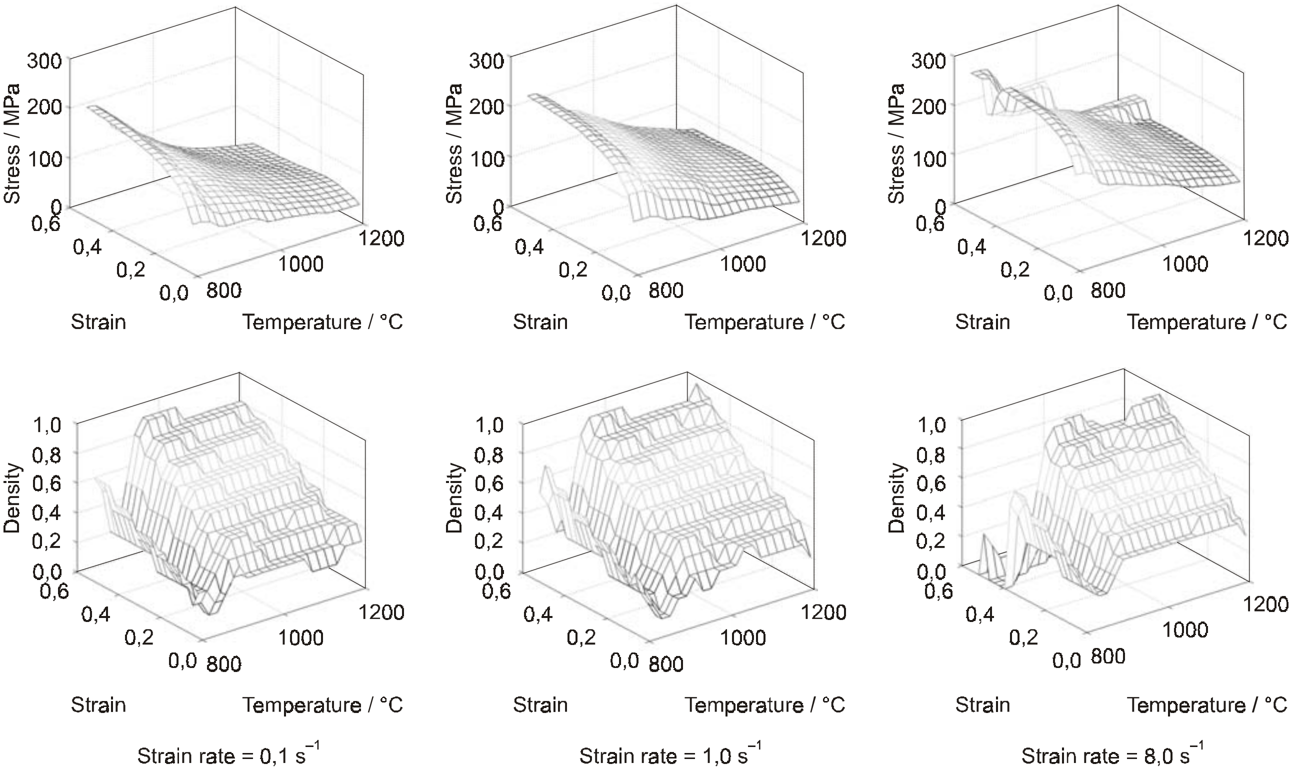

Figure 6. **Surface plot of hot flow curves and density of data for tool steel as a function of strain and temperature, using a non-constant smoothing parameter ($w_{\varepsilon(\varepsilon=0.01)}=0,005$; $w_{\varepsilon(\varepsilon=0.52)}=0,015$,; $w_{\varepsilon'(\varepsilon'=0.1)}=0,015$; $w_T=0,05$) - axonometric view**

Slika 6. **Ploštinski dijagram krivulja zatezanja u vrućem i gustoća podataka za alatni čelik kao funkcija deformacije i temperature upotrebom nestalog parametra glatkoće ($w_{\varepsilon(\varepsilon=0.01)}=0,005$; $w_{\varepsilon(\varepsilon=0.52)}=0,015$,; $w_{\varepsilon'(\varepsilon'=0.1)}=0,015$; $w_T=0,05$) - aksonometrički pogled**

there is a clear indication of lack of data. Small $\hat{\rho}_k$ values indicate the region of extrapolated data. Such case is observed for strain rate 8,0 s^{-1} at strains larger than 0,4.

Determination of activation energy from hyperbolic-sine equation

During the deformation the dynamic recovery (DRV) may be the only softening process, or it may be accompanied by dynamic re-crystallisation (DRX) - in both cases we can satisfyingly describe the dependence of flow stress in stationary condition on velocity of deformation $\dot{\varepsilon}$ and temperature T with the empirical hyperbolic-sine equation [31 - 33]

$$\dot{\varepsilon} = A \cdot (\sinh \alpha\sigma)^n \exp\left(-\frac{Q}{RT}\right) \tag{7}$$

where A, α and n are temperature-independent constants and Q is activation energy. We can use equation (7) for description of peak flow stresses dependency on velocity of deformation and temperature as well. The parameters in this equation are determined by the flow curves at various temperatures and velocities of deformation. First we find a logarithm of this equation and properly arrange the elements, and then we define function χ^2, that minimizes the difference between the calculated and measured values of flow stress

$$\chi^2 = \sum_{i=1}^{N} \frac{(z_i - a_1 x_i - a_2 y_i - a_3)^2}{e_i^2} \tag{8}$$

where N is the number of measurements, $z_i = \ln(\sinh \alpha\sigma_i)$, $x_i = \ln \dot{\varepsilon}_i$ and $y_i = 10^4\, T^{-1}$. Parameter $a_1 = n^{-1}$, $a_2 = 10^{-4} Q n^{-1} R^{-1}$ and $a_3 = n^{-1} \ln A$. For the error calculation we took into account only measurement errors of the parameter z_i, given by $e_i = \alpha\, e_i^{\sigma} \coth \alpha\sigma_i$, where e_i^{σ} are the measurement errors of the flow stress. The details of the minimization procedure of the above expression (8) are given elsewhere [25]. χ^2 has a minimum for Q = 367 kJ mol^{-1}, α = 0,0092 MPa^{-1}, n = 5,77 and A = 6,7 10^{13} s^{-1}. For these parameters a comparison between the calculated and measured dependence of peak stress on temperature for three different strain rates is shown on Figure 7a. and a comparison between the calculated and measured peak stresses on Figure 7b. McQueen et all proposed for the steel the use of the value α = 0,012 MPa^{-1}. In such case we get a bit higher value for activation energy Q = 374 kJ mol^{-1}, the calculated values of the other two parameters are n = 4,88 in A = 2,04 10^{13} s^{-1}. The matching between the measured and calculated values of peak flow stresses for the McQueen's example is χ^2 = 0,15 and for ours χ^2 = 0,12.

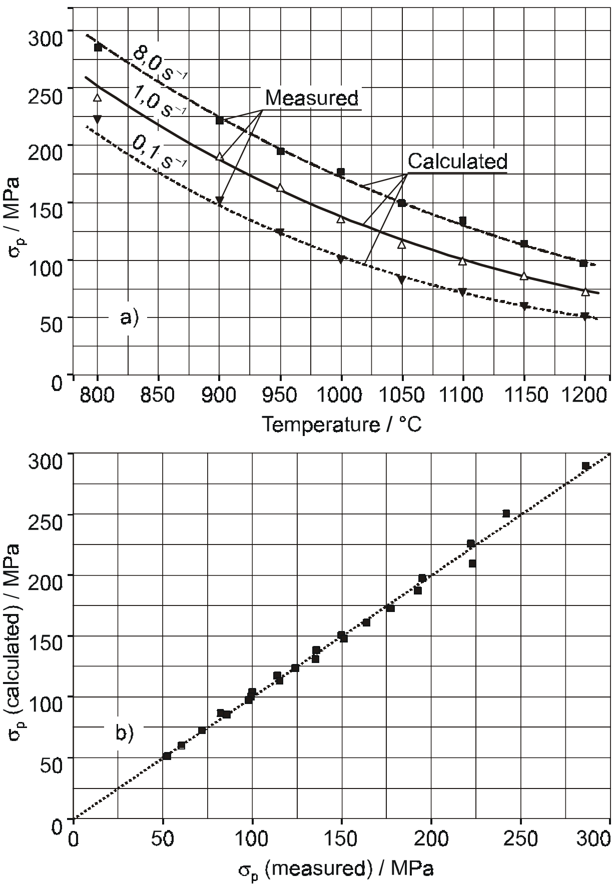

Figure 7. **Comparison between measured and calculated dependence of a) peak stress on temperature for three different strain rates of 0,1 s^{-1}, 1,0 s^{-1} and 8,0 s^{-1}, and b) a comparison between measured and calculated peak stresses**

Slika 7. **Usporedba između izmjerenih i izračunatih ovisnosti: a) pik naprezanja od temperature za tri različite brzine deformacije 0,1 s^{-1}, 1,0 s^{-1} i 8,0 s^{-1}; b) usporedba između izmjerenih i izračunatih pikova naprezanja**

CONSLUSIONS

For the tool steel we performed hot compression tests by means of Gleeble 1500 thermo mechanical simulator, namely for three various deformation velocities (0,1, 1,0 in 8,0 s^{-1}) in the temperature range 800 - 1200 °C. Due to relatively big errors (2 - 60 %) at predicting the flow curves by means of empirical models and due to difficulties with application of the BP NN (problem-oriented learning) we decided to use the CAE NN for the represented study. We considered the constant and non-constant smoothness parameter. In case of applying the method of non-constant smoothness parameter we get better agreement between the factual and predicted results (up to 3,4 %). The accuracy attained ranges from 0 to 5 %, which already represents generally adopted accuracy in today's requirements regarding the optimization of hot forming technology. Still more, the attained accuracy is even better than in case of the application of the BP NN for predicting the flow curves in tool steel (up to 7 %). With the newly proposed measure it is furthermore possible to define the reliability of the attained results as well. An additional advantage of applying the CAE NN - if compared with the usual BP NN - is the fact, that we are not limited by the number of influential parameters [34, 35]; consequently it means the ability of inclusion of variations in chemical compositions of steel that occur from charge to charge and the consideration of phase transformations in the temperature range of hot metal forming. All these information are needed to meet the nowadays requirements on further optimisation of the forming processes, i.e. hot rolling etc.

The activation energy and other parameters of the hyperbolic-sine equation have been calculated by applying the method proposed by McQueen et al. and the recently proposed method of Kugler et al. The latter yields very good results in predicting the peaks of the flow curves. The opinion of the authors is that it is best to apply the empirical hyperbolic-sine equation in such a way, that the parameter α of the proposed equation is determined at minimal χ^2, and not by means of a value, prescribed in advance. Even though the mentioned equation is empirical and its parameters do not have a clear physical background, it nevertheless excels in the fact that it offers us the possibility to easily describe the dependences of maximum or steady flow stresses regarding the deformation and temperature velocities at a wide interval of their variability.

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